Insper and NOVA School of Business and Economics

Masters in Economics - Double Degree Program

João Paulo de Faria Tavares Rabe

MEASURING CORE INFLATION IN BRAZIL USING AN SVAR APPROACH.

São Paulo / Lisbon

2020

João Paulo de Faria Tavares Rabe

MEASURING CORE INFLATION IN BRAZIL USING AN SVAR APPROACH.

Work Project presented to the Double Degree Masters in Economics Program from Insper and NOVA School of Business and Economics as a part of the prerequisites for the entitlement as Master in Economics.

Area of expertise: Macroeconomics and Financial Markets

Advisor: **Prof. Dr. Diogo Abry Guillen**

Co-Advisor: **Prof. Dr. André C. Silva**

São Paulo / Lisbon

2020

RABE, João Paulo de Faria Tavares

MEASURING CORE INFLATION IN BRAZIL USING AN SVAR APPROACH. / João Paulo de Faria Tavares Rabe / Advisor: Prof. Dr. Diogo Abry Guillen – Insper / Co-Advisor: Prof. Dr. André C. Silva – Nova SBE. 2020

Work Project (Masters – Masters in Economics. Area of expertise: Macroeconomics and Financial Markets) – Insper Instituto de Ensino e Pesquisa and NOVA School of Business and Economics.

1. Inflation; 2. Core Inflation; 3. SVAR; 4. Brazil; 5. Long-run Phillips Curve.

APPROVAL SHEET

João Paulo de Faria Tavares Rabe
MEASURING CORE INFLATION IN BRAZIL USING AN SVAR APPROACH.

Work Project presented to the Double Degree Masters in Economics Program from Insper and NOVA School of Business and Economics as a part of the pre requisites for the entitlement as a Master in Economics.

Area of expertise: Macroeconomics and Financial Markets

Approved in:

Committee

Prof. Dr. Diogo Abry Guillen Institution: Insper	**Signature:** ____________________________
Prof. Dr. André Castro Silva Institution: NOVA SBE	**Signature:** ____________________________
Prof. Dr. Institution:	**Signature:** ____________________________
Prof. Dr. Institution:	**Signature:** ____________________________

ABSTRACT

RABE, João Paulo de Faria Tavares. **Measuring Core Inflation in Brazil Using an SVAR Approach**. Master's Thesis – Insper, São Paulo, 2020 and NOVA School of Business and Economics, Lisbon, 2020.

The main objective of this paper is to present a new measure of core inflation for the Brazilian economy. Different from the statistical and atheoretical measures usually used by the Central Bank of Brazil, the methodology is based on Quah and Vahey (1995) and is backed by the economic theory that the Phillips Curve is vertical in the long-run, therefore the core inflation is calculated as the component of the measure inflation that does not impact the output level in the long-run. This is an approach almost not explored in Brazil, and the results have shown that could be beneficial if included in the set of measures followed by the Central Bank. In order to calculate this core measure, two Structural Vector-autoregression models are used. Firstly, it is estimated the bivariate model proposed by Quah and Vahey (1995), in which the (log) difference of output level and the (log) difference of price level are used aiming to identify core and non-core shocks. The results, as discussed in the related literature, showed that both structural shocks have a similar pattern to what the theory identifies as positive demand and supply shocks. Further, in light of Bjørnland (2000) and Martel (2008), a commodity price index is added to better identify the shocks affecting the system. Both models point out that the measured inflation and the core inflation measures follow the same trend, whereas short-term inflation is mainly due to supply shocks. Although there seems not to be a consensus as to what is the best methodology to calculate a core inflation measure, hence the literature recommends that a core inflation measure should have some specific characteristics. Therefore, a comparison among the measures produced by the SVAR models and the ones typically used by the Central Bank of Brazil is conducted to evaluate these features. The results pointed out that among the core measure analyzed the only ones systematically unbiased are produced by the SVAR approach. Moreover, the SVAR methodology also showed more gains in tracking the inflation trend than the exclusion methods, whereas the core measure based on trimmed means – by construction - is the one with the lowest error. Finally, the core measures with the best forecast (out-of-sample) performance are the SVAR trivariate system, the Ex3, and the P55.

Keywords: Inflation; Core Inflation; SVAR; Brazil; Long-run Phillips Curve.

Executive Summary

Summary

1. Introduction

The international literature on core inflation measures is widespread, whereas it has been discussed for decades it is still a subject that is constantly being studied and updated. A common view in the literature is that there is no consensus on which is the best approach to measure core inflation, although the central banks around the world seem to have converged to a selected range of methodologies (Exclusion and Trimmed means). Brazil is no exception, the most recent inflation report shows that the BCB[1] keeps a similar set of core measures that the international literature discusses.

According to Figueiredo (2001), for a Central Bank following an inflation target regime, it is necessary to have an accurate and reliable measure of core inflation. To either detect particular movements in prices or conduct official communications more transparently.

The inflation target is determined based on a specific price index, however, as stated by Martel (2008), the usefulness of this index for monetary policy could be misleading as it is polluted by specific and temporary shocks. Therefore, the study of core inflation could be helpful in accommodating a balanced monetary policy. Regarding this, Figueiredo (2001) mentioned that the core component of inflation is an important tool as it enables the monetary authorities to distinguish the inflationary movements into shocks (that is, noise) and signal (core movements/trend inflation). By definition, as the noise shocks are accounts as temporary shocks, they quickly dissipate with no impact on inflationary expectations, hence there is no need for monetary policy action.

Frequently, despite the importance of the core inflation for the decision of the policymakers, as presented by both Rich and Steindel (2005) and Silva Filho and Figueiredo (2014a) there is no clear evidence of a unique measure of core inflation capable to completely filter the temporary shocks, thus the Central Banks customarily use more than only one measure and are always reviewing the ones that they use.

Regarding that, Brazil Central Bank in its June 2020 inflation report (BCB 2020a) introduced a new core measure and excluded three others that were in use, leaving officially a total of five different measures that are published on monthly basis along with the official price index used for the inflation target regime.

Nevertheless, the criticism regarding these core measures is a constant issue with each one being judge based on different criteria. Facing that, Mattos (2018), Machado *et al* (2020), and Da Silva (2020) sought to introduce new methodologies to core inflation discussion in Brazil, among

[1] Central Bank of Brazil or Banco Central do Brasil.

these papers there is a consensus that each of these proposed new measures positively contributes in some feature for the set of core measures already in use by the BCB. However, none of the papers are emphatic to the point that the others approach (the ones often used) should be disregard by the BCB. Coupled with this reasoning, this paper aims to contribute to this debate by calculating a core measure following the methodology presented by Quah and Vahey (1995) and understanding how is the relative performance compared to the commonly used core measures.

Quah and Vahey's (1995) methodology seeks to estimate a core measure backed by economic theory. According to their approach, the core inflation is computed as the part of the measured inflation that has no long-run impact on real output, therefore consistent with the economic view that the Phillips curve is vertical in the long-run. The research proposal is to conduct an estimation using a SVAR approach with two different formalizations of the structural model. The first one follows the model proposed by Quah and Vahey (1995) and the second expand this model by including a commodity index as done by Bjørnland (2000) and Martel (2008).

As a result, the impulse response analysis showed that both a core and non-core shock have a temporary effect on inflation with the former increasing inflation and the latter reducing it. Moreover, a core shock – by construction – does not affect the output level in the long-run, while a non-core shock increases permanently the GDP level. Therefore, as pointed by Bjørnland (2000), a non-core shock could be considered as a beneficial supply shock increasing output permanently and reducing inflation.

Furthermore, both core measures and the measured inflation (IPCA) seem to follow the same trend, whereas the short-term inflation is mainly explained by supply shocks – in either of the frameworks (bivariate or trivariate). Therefore, the measured inflation – considering the estimation period – appears to overestimate the core measure during negative supply shock and underestimate it in periods with a positive supply shock.

The remainder organization of the paper has the following structure: the next section introduces a literature review discussing how core inflation is defined and shows different approaches to calculate and evaluate each one of them. Next, it is presented which is the set of methodologies used by the BCB with some criticism made by recent papers. In sequence, the econometric model of Quah and Vahey (1995) – as well as the economic theory that supports it - is discussed with another approach that sought to extend this methodology. Finally, the results and conclusions are presented.

2. Literature Review, Model, and Methodology.

In this section, firstly one of the most used definitions of core inflation in the literature is discussed, then, according to this definition, some of the most used methodologies to estimate this unobserved variable are presented. As there are so many different approaches, it is presented what the literature discusses as the desirable characteristics that a core inflation measure should have. Further, a brief discussion is made about the set of core inflation measures used by the BCB along with a review of recent papers that sought to present new approaches to calculating the core inflation in Brazil. Finally, Quah and Vahey (1995) methodology is presented together with the economic theory that supports it.

2.1. Core Inflation: Definition and Different measures.

According to Wayne (1999), the analysis of core inflation has been influencing the decision of the Central banks since the 1970s. Yet, there is still no consensus on what is the best approach to measure core inflation. With the same reasoning, Bryan and Cecchetti (1993) argue that although the term core inflation is widespread, there seems to be no clear definition. Moreover, Silva Filho and Figueiredo (2011) argue that there is not even a theoretical definition of core inflation that is fully accepted. However, the literature has not reached a consensus, the most diffused definition states that core inflation is what remains after the noise component is completed eliminated. Formally, Silva Filho and Figueiredo (2011) presents the following equation, in which the inflation of an individual good or service (π_i) is divided into a common component ($\tilde{\pi}$) and in a specific part (ε_i).

$$\pi_{i,t} = \tilde{\pi}_t + \varepsilon_{i,t} \tag{2.1.1}$$

Therefore, when successfully isolated the specific part ε_i, the core inflation (π^c) in each instant of time will be given by the common component, that is, $\pi_t^c = \tilde{\pi}_t$. Given this definition, the discussion becomes how to measure this common trend, hence the core measures differences become a result of the different pieces of information that are used to calculate them.

Figueiredo (2001) and Wynne (1999) provides an overview of the different approaches used to calculate the core measure. According to the authors, the first attempt to isolate the noise component was put in practice during the 1970s, in which the most volatile elements from the price index are excluded (hence, the name method by Exclusion), this methodology continues to be adopted nowadays as several central banks remain to use it, mainly because it is easy to calculate and to be understood by the public, albeit there is no economic theory supporting it.

Although, as mentioned by Figueiredo (2001) using the exclusion method, relevant information can be lost. Therefore, Laflèche (1997) recommends another methodology, in which these items are not excluded, but re-weighted in relation to their volatility. With this approach, their relevance in the core measure is reduced whilst any relevant information regarding these items can influence the core measure yet. Figueiredo (2001), states that these new weights can be calculated using two complementary proposals: i) following Marques et al (2000) they are a result of the inverse of their volatility, and ii) according to Laflèche (1997) and Deutsche Bundesbank (2000) it is possible to use the double weighting method in which the volatility weights are combined with the expenditures weights.

In addition, a different procedure, shown by Bryan and Cecchetti (1993) - the so-called Limited Information Estimators (LIE) - is related to reducing the importance of items in the tail of the distribution; examples of this are the trimmed-mean and the weighted median. This kind of approach has a statistical appeal that the noise part ε_i is not normally distributed, and there is some kind of skewness in inflation distribution.

The different methods explained so far are concentrated in a cross-section time perspective applied to the individual price level, that is, the calculations are done considering only contemporaneous price data. By turning to the time series approaches, according to Wynne (1999) and as outlined in Table 1, there are more three different procedures.

Table 1 – Approaches to core inflation measurement.

		Time perspective	
		Cross-Section	Time Series
Raw Data	Individual Prices changes	Exclusion Methods, LIE and Double Weighted Index	DFI
	Headline Inflation rate	NA	Moving averages and Statistical Filters
	Price data (either headline or disaggregated) plus other aggregates	NA	SVAR.

Source: Wynne (1999).

The first one concerns to smoothing methods applied to the headline inflation; this encompasses from moving averages to statistical filters as, for example, the Hodrick- Prescott filter.

Furthermore, the second procedure seeks to merge contemporaneous individual information and time series to estimate the core inflation, that is, they explore in time the behavior of the different components of the price index (Figueiredo, 2001). The methodology called Dynamic Factors Index (DFI), following Wynne (1999), was introduced by Bryan and Cecchetti (1993) and Cecchetti (1997). Exploring the idea that the common component ($\tilde{\pi}_t$) is unobserved, this model tries to filter - from the individual components of the price index - the unobserved common stochastic component. Yet this procedure fails to deliver a core measure reasoned in economic theory.

Finally, we have the SVAR models presented by Quah and Vahey (1995). This methodology is supported by the theory of long-run verticality of the Phillips Curve. They identify the VAR with long-run restrictions to be able to estimate the core inflation that is determined as the component of inflation that does not impact the real output in the long run.

2.2. Evaluating the Core Inflation Measures.

Along with such a range of different methods, the challenge arises of which to choose. Facing that, Wynne (1999) enumerates a total of six desirable characteristics that a core measure should have.

The first one is *Computable in real time*, almost all the measures presented before meets this criterion except the statistical filters based on centered moving average (i.e. the band-pass filter). The second explores the idea that the measure should be *forward-looking*, although all the core measures may be capable of forecast the headline inflation the only methodology that - by construction - provides a core inflation with this feature are the ones based on SVAR. The third one is based on the capacity that the measure presents *track record*, that is, how well the core measure explains past inflation.

The fourth and the fifth characteristics use as a premise that the Central bank has the intention of using the computed core as part of the regular communication to the regular public, following this, Wynne (1999) argues that the measure should be *understandable by the public* and that *the history does not change*, once the premise is valid it is possible to conclude that any core measure based on econometric methods is compromised, therefore is necessary to access in which degree past estimates changes as new information arrives. Whereas the only methodology that can be understood by the general public is the one based on exclusion methods.

Lastly, the core measure may be backed by economic theory, ideally on money neutrality (Wynne, 1999). Therefore, the only measure that meets this criterion is the one based on SVAR models, essentially the ones that follow the identification scheme proposed by Quah and Vahey (1995).

The discussion above enhances the conclusion from Figueiredo (2001), that is, in the end, the best choice of core measure relies on the Central Bank objectives. If the Central Bank seeks to anchor the inflation expectations, thus the core inflation should be used in official communications which implies the need to use measures that are understandable by the public in general and that have consistency when new information arrives (i.e. the history does not change). In contrast, Figueiredo (2001) also points out that facing a context in which the Central Bank has an objective to use the core measure as an intermediate target, then a more refined approach can be used, for example, the ones based on econometric and theoretical models.

Correspondingly, Laflèche (1997) argues that as there is no consensus regarding which is the best approach to measure the core inflation and since the use of each one may be pegged to the Central Bank objective, a range of measures should be the most suitable, hence when this set of core measures jointly moves to a direction the monetary policy could interpret it as a strong signal regarding the inflation trend. On the other hand, disparate movements ought to be analyzed in order to understand which is the source of it.

In an effort to understand how widespread is the different approaches to measure the core inflation in the world Mattos (2018) compiles Table 2. At first glance, Laflèche's (1997) argument strikes out, that is, among these 20 selected countries all central banks follow more than one core measure, also it is clear that almost all make use of the Exclusion methods in accordance with the idea that they are easier understandable by the public in general. Furthermore, among these 20 countries, only five of them make use of models to estimate the core measure.

Table 2 – Core Inflation around the world

	EX	DP	MA	ME	Model
Australia	x		x	x	
South Africa	x		x		
Argentina	x		x		x
Bolivia	x		x		
Brazil	x	x	x	x	
Canada	x	x	x	x	x
Chile	x				
Colombia	x		x		
Ecuador	x				
United States	x		x	x	
Japan			x	x	
Mexico	x		x		
Norway	x		x	x	
New Zealand	x		x	x	x
Paraguay	x	x	x		
Peru	x				x
Sweden		x	x		
Switzerland	x		x		
Uruguay	x				
Venezuela	x				
Euro (area)	x		x	x	x

Ex: Core by exclusion; **DP**: Core by double-weighting;
MA: Core by trimmed means. **ME**: Median.
Model: Dinamic Factors, Principal Components or VAR.
Source: Mattos (2018)
completed with ECB (2018) as done by BCB (2020a) .

2.3. Core Inflation in Brazil.

In Brazil, the Central Bank uses a set of five core measures that were recently revised[2], they are calculated based on the IPCA[3], the price index used by the monetary policy to guide the decisions following the inflation target regime. This range of measures is composed of two exclusion methods (Ex-0 and Ex-3) and three statistical: two trimmed mean measures (MS and P-55), and one double-weighted measure (DP). According to BCB (2020a), each core used as a tool to conduct the monetary policy has a set of particular characteristics. The exclusion methods are easier to communicate and tend to be more correlated with the business cycle, at the same time the statistical measures have less bias and variance, whereas follows closely the inflation trend.

Furthermore, in Brazil, some recent papers have explored different approaches to construct a measure of core inflation. Mattos (2018), after concluding that the set of core measures used by the BCB do not properly capture the trend of inflation, discusses two additional methodologies. The first one tries to improve the trimmed mean core by smoothing it, that is, the objective is to remove the seasonality and the remaining noise which are concealing the trend inflation – the study

[2] BCB (2020), inflation report june/2020

[3] IPCA stands for "Índice de Preços ao Consumidor Amplo" (Extended National Consumer Price Index), it is calculated by IBGE a statistical bureau agency in Brazil.

purpose of Mattos (2018). The second one is based on a statistical model that is known as *score driven models* or *Dynamic Conditional Score (DCS)* this methodology seeks to decompose the price index inflation into some unobserved components, and these components are a function of the *scores* of the conditional distribution of observations. As a conclusion, Mattos (2018) presents that both measures provide clearer information regarding the inflation trend and about future movements, whereas - between the two approaches - the DCS is better in analyzing the recent inflation trend as past information does not have much influence on its construction.

Machado *et al* (2020), criticize the usual core measures applied by the central banks around the world stating that in their calculations in general the time dimension of price developments is not considered, thus useful information that is disposed over time in data movements is neglected, that is, as some components are predetermined to be removed earlier signals of changes in inflation could be also excluded. Therefore, they propose to use the Dynamic Common Factor approach based on Cristadoro *et al* (2005), this methodology simultaneously takes into account the cross-section and time-series dimensions of the panel data and seems to be pioneered in Brazil. As a result, the authors obtained that this measure should be useful to integrate the set of core measures followed by the Central Bank once it shows some of the desirable features that are expected: unbiasedness, tracks the inflation trend, have a good performance in forecasting and have a relatively high sensibility to the business cycle. Although, it is not easier understandable by the public.

Da Silva (2020), is another one to criticize the core measures frequently followed by the Central Bank of Brazil. Argues that whereas this range of core inflation shows less volatility than the headline inflation, some of them do not meet the formal requirements that the literature suggests in order to be considered a good core measure. Therefore, Da Silva (2020) seeks to estimate an alternative measure using statistical applications of wavelet techniques. As a result, it is obtained that this methodology has the potential to improve the often published core measures in terms of inflation trend and forecasting.

Finally, what concerns the applied literature regarding the core inflation in Brazil, a former paper from Picchetti and Kanczuk (2001) already used Quah and Vahey's (1995) methodology to estimate the core inflation in Brazil. It is obtained that the core measure seems to have a good performance indicating the turning points of the measured inflation, whilst appear to filter out the supply shocks identify in Bodansky *et al* (2001). Furthermore, they conclude that the SVAR methodology used would benefit - in further studies – from the inclusion of more variables, and by accounting for events that could generate regime-switching.

2.4. The Structural VAR Model and the economic theory background.

Quah and Vahey (1995), in their seminal paper, begin by arguing that the approaches often used in the literature to calculate the underlying inflation had been to remove in some *ad hoc* manner the noise component, as the remaining portion is expected to be a solid estimation of the core inflation. As an example of these approaches is mentioned the smoothing methods (i.e. moving averages) or what they called "structural time series modeling". The latter, according to Quah and Vahey (1995), requires that the researcher define a functional form for the process, usually, the hypothesis is that it follows a random walk, then it is necessary to use a Kalman Filter to process and identify the components from the observed inflation series. The criticism concern these measures is that they involve premises with almost no economic interpretation, that is, there is no economic reasoning supporting that changes in core inflation should follow a random walk or that the underlying inflation is "the product of some arbitrary smoothing procedure".

Raising these concerns Quah and Vahey (1995) introduce another procedure to measure the core inflation, according to their methodology the underlying inflation is given by the component of measure inflation that has no medium to long-run impact on real output. This interpretation is backed by the theory that the Phillips Curve is vertical in the long-run, that is, once wage and financial contracts have been fixed, changes in inflation (or core inflation) could be benign for the real economy. For a broader understanding of this dynamic, it is worth to analyze how the adjustment will occur following a Keynesian "story" as presented by Falk and Lee (1999), an inflation (or core inflation) shock will raise the prices, although as the contracts were already written (and rewriting them might be time-consuming) the real wages will fall - following the nominal rigidity in the short-run. Therefore, if in the short-run employment is only determined by labor demand the employment level will rise boosting the real economy.

In order to investigate the validity of a vertical long-run Phillips curve, Benati (2015) use a Structural VAR identified with long-run restriction or a mix of sign restriction and long-run restriction, the experiment is conducted for some selected countries as of US, Canada, UK, Australia, and the Euro area. As a result, it is obtained that the null hypothesis of the vertical long-run Phillips curve can not be rejected for either country with the results been robust to different specifications of the shocks in the system, albeit the author mentions that the uncertainty level in the estimations is high.

Regarding Brazil, there seems to be no specific study evaluating the feasibility of the long-run Phillips curve. Nevertheless, Schwartzman (2006) by estimating some disaggregated Phillips curve for the Brazilian economy concludes that are pieces of evidence in favor of its use, moreover, the Central Bank also uses the specification of a long-run vertical Phillips curve in his semi-structural model (BCB, 2018). Both arguments, even though do not present an emphatic conclusion regarding the use of this theory, should help us suppose that this theory is also valid for the Brazilian economy.

In a formal definition, the new Keynesian Phillips curve, as shown by Galí (2008), can be expressed in the following equation, in which $E_t\{\pi_{t+1}\}$ is the expected inflation one period ahead and $\tilde{y}_t$ is the output gap.

$$\pi_t = \beta E_t\{\pi_{t+1}\} + k\tilde{y}_t \tag{2.4.1}$$

Therefore, if we solve the equation (2.4.1) to the stationary state we get the equation (2.4.2).

$$\pi = \frac{k}{(1-\beta)}\tilde{y} \equiv \varphi\tilde{y} \tag{2.4.2}$$

By assuming the long-run verticality, it is necessary to impose that β is close to 1, thus it is impossible to achieve an equilibrium where the output is different than the potential - as this will imply an explosive behavior of the inflation once the parameter φ will converge to infinite. Solving inversely the equation (2.4.2) it is provided that the relation between the output gap and the inflation – in the stationary state – is given by $1/\varphi$ that is, equal to zero. Hence, this relation implies that, in the stationary state, inflation does not impact the level of output; it is this economic theory that supports the core inflation identification of Quah and Vahey (1995).

In order to conduct their core inflation estimations, Quah and Vahey (1995) use a bivariate Structural VAR composed of inflation and a measure of activity. The identification procedure follows Blanchard and Quah (1989) by imposing long-run restrictions. It is assumed that the observed fluctuation of the measured inflation is influenced by two disturbances: core shocks and non-core shocks and these structural shocks are assumed to be uncorrelated in all leads and lags, pairwise orthogonal, and to have variance equal to one. These structural shocks are distinguished in how they affect the output. One of these disturbances is unrestricted, so the effects in inflation and activity are not predetermined, whereas the other disturbance is restricted to not impact the activity level in the medium to long-run. The underlying inflation is then calculated from the impacts of the later disturbance. Appendix A presents the technicalities of the methodologies used.

3. Data and Model Estimation.

3.1. The Choice of Variables and the Data Source.

As mentioned, two models will be estimated. The first one is related to the bivariate structural VAR approach specified by Quah and Vahey (1995), whilst the second one expands this methodology and includes a third variable as done by Bjørnland (2000) and Martel (2008). Therefore, to adapt these models to the Brazilian economy one needs to define three variables to capture the commodities prices, output level, and the price level, respectively.

Firstly, instead of using the energy price as done by both authors, the choice here is to use the Commodity Price Index[4] calculated by the Central Bank of Brazil. The index is published monthly and – in addition to Energy prices - Agricultural and Metal prices are part of its composition[5]. The individual weights are determined based on the relevance of each component to the dynamics of domestic inflation. Therefore, using this index it is possible to capture possible shocks that influence the inflation expectation, whereas it is possible to comprise the real effects on the economy through higher exports and higher government revenues[6].

Secondly, in order to represent the output variable, possible candidates are the GDP or the IBC-Br[7]. The former is only available quarterly whilst the latter is calculated and used by the BCB to evaluate the activity level monthly and, more important, it is built to mimic the path of measured GDP. As the usefulness of a core inflation measure for the monetary policy is pegged on how often the data is available - that is, how frequently the Central Bank can evaluate the core inflation - the IBC-Br seems to be a worthy selection, without inducing any loss of generality as methodologies using the industrial production.

Finally, to depict the price level, the variable choice is more straightforward. Once, the main objective of a core measure is to be an instrument helping to conduct the monetary policy, the rational selection is to base the estimations in the same measured price index used in the inflation target regime, namely, the IPCA[8].

[4] IC-Br (Commodity Index – Brazil). Avaible in the *Time Series Management System* of BCB under code 27574. More information about this Index can be accessed in BCB (2010) and BCB (2017).

[5] the international price of each component is converted to Brazilian reais.

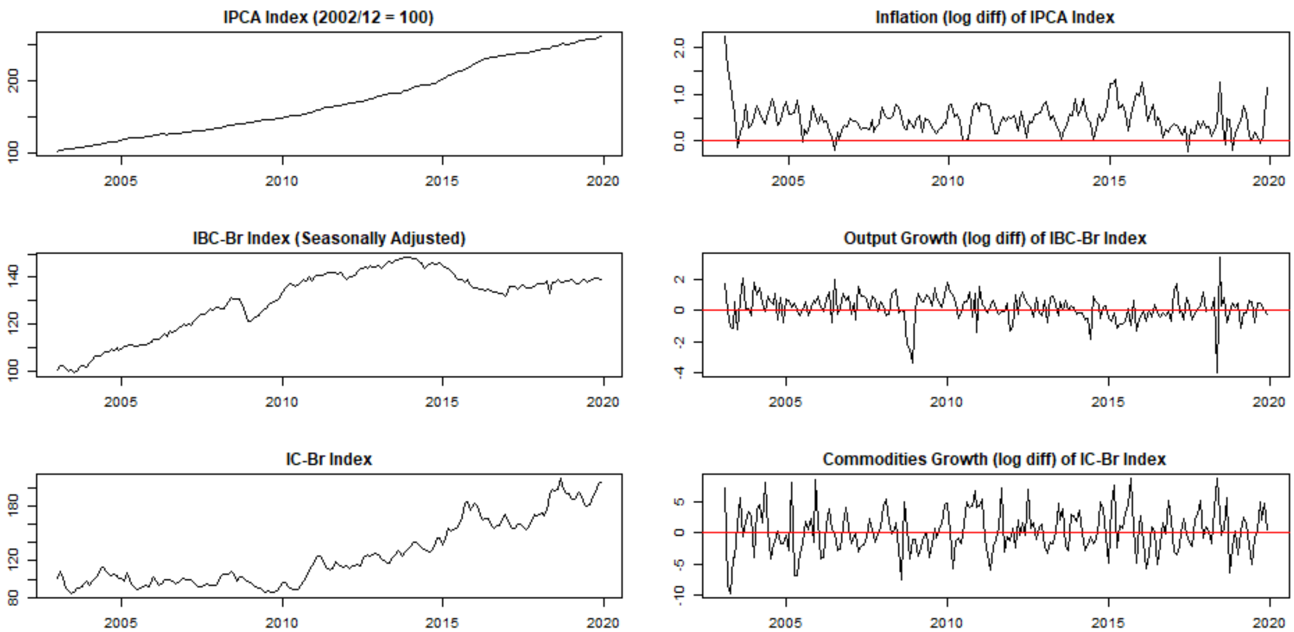
[6] Considering Brazil a small exporter.

[7] Central Bank Economic Activity Index (IBC-Br). Avaible in the *Time Series Management System* of BCB under code 24364.

[8] Broad National Consumer Price Index (IPCA), calculated by IBGE. Avaible in the *Time Series Management System* of BCB under code 433.

Figure 1 shows the level of the series that are being considered as well as the first (log) difference of each one. The period span from the first month of 2003 through December 2019, as the IBC-Br starts in January 2003.

Figure 1 – Data Set Graphics.



3.2. Time Series Properties of the Data.

As supposed by Quah and Vahey's (1995) model, the time series of the level of output and prices have a stochastic trend, whilst are not cointegrated. The same is surmised by Bjørnland (2000) and Martel (2008) for the entire system when they included energy prices. Therefore, it is necessary to evaluate from the series represented in Figure 1 if, in level, all are I(1) whereas in the first difference they are I(0). At the same time, the bivariate system or the trivariate system should not present any cointegration vector.

These proprieties are accessed in Tables 3. The ADF tests are conducted to check for the presence of unit roots, and the Johansen cointegration test checks for the presence of cointegration vectors.

Table 3 – Testing the Data Series Set Properties.

System		Variables[a]	ADF Test - (A) Equation	Lags	Statistic	Critical Value*	Conclusion
Trivariate	Bivariate	IPCA	drift	1	<0.01	-2.88	I(1)
		IBC-Br	drift	1	-2.43		I(1)
		IC-Br	drift	1	-0.4		I(1)
Trivariate	Bivariate	Δ IPCA	drift	1	-7.44	-2.88	I(0)
		Δ IBC-Br	drift	1	-8.14		I(0)
		Δ IC-Br	drift	1	-10.12		I(0)

[a] The variables are being considered in (log) level. Δ indicates the first difference of the (log) level.

* Critical Value considered at the 5% level of significance. Critical values are taken from Hamilton (1994) and Dickey and Fuller(1981).

			Johansen Cointegration Test - (B)				
			Trace		Maximum Eingenvalue		
		H0	Statistic	Critical Value*	Statistic	Critical Value*	**Conclusion**
System[a]	Bivariate**	r = 0	18.55	25.32	12.68	18.96	**No cointegration Vector.**
		r ≤ 1	5.87	12.25	5.87	12.25	
	Trivariate***	r = 0	39.81	42.44	23.23	25.54	**No cointegration Vector.**
		r ≤ 1	16.57	25.32	12.35	18.96	
		r ≤ 2	4.23	12.25	4.23	12.25	

[a] The variables are being considered in (log) level

* Critical Value considered at the 5% level of significance. Osterwald-Lenum (1992) critical values.

** Number of lags equal to 10.

*** Number of lags equal to 2.

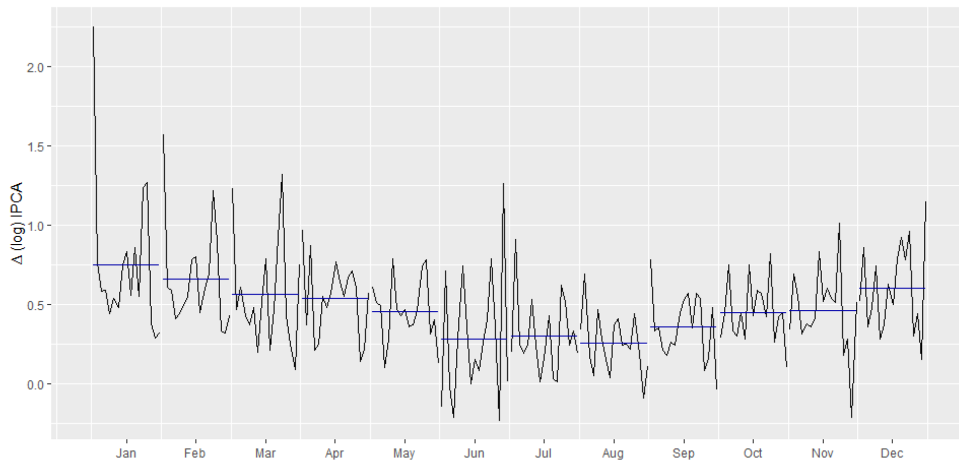
As shown in Table 3 – Panel A, there is no statistical evidence for any of the series (in log level) in favor of rejecting the hypothesis that they are a unit-root process, hence the series in (log) level are considered non-stationary. Although it is possible to reject the null hypothesis of the ADF test when took the first difference of the series, thus the conclusion from the previous procedure points out that the order of integration from each one of the three series should be equal to one.

As the series in (log) level are I(1) it is possible to conduct the Johansen Cointegration Test – in panel B from Table 3. The conclusion, for both systems, is that there is no cointegration among the variables. Therefore, as the variables – in log (level) – are I(1) and not cointegrated it is possible to write the VAR in the first difference as described by the methodology.

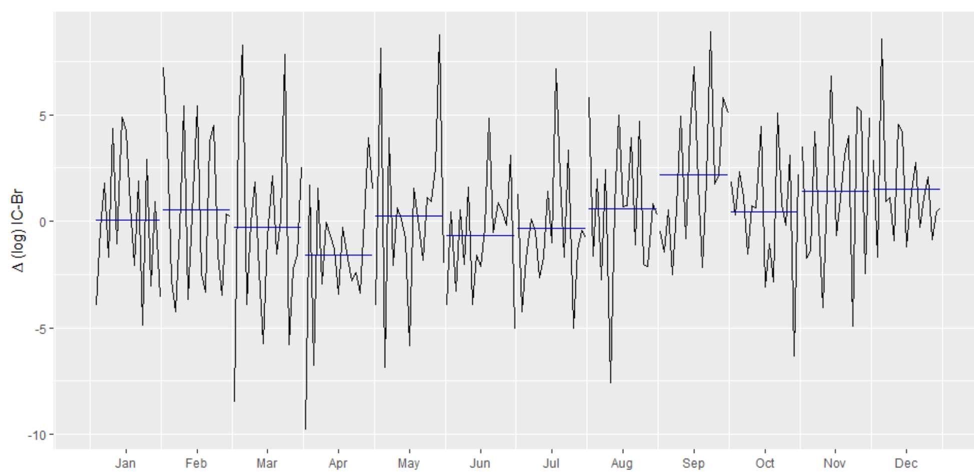
Furthermore, it is worthy to notice that the only series with seasonal adjust is the IBC-Br, which is evident when analyzing Figure 2. Therefore, supporting the idea of include seasonal dummies in the model.

Figure 2 – Seasonal Plot

(a) Δ (log) IPCA



(b) Δ (log) IC-Br



3.3. Estimation.

Using the proprieties of the data shown in section 3.2 it is possible to estimate the VAR in the first (log) difference of the variables. The lag order of the models was determined based on the results in Table 4. As shown, both AIC and FPE points to five and four lags for the bivariate and trivariate system, respectively. Whereas HQ and SC suggest the use of one lag for both models. Estimations with only one lag were not able to eliminate the presence of serial correlation in both models, so it was decided to estimate the bivariate system with five lags and for the trivariate, four lags were used.

In addition, both estimates included a constant, seasonal dummies, and dummies for specific events such as the 2008 financial crisis and the trucker strike in 2018. Considering the lag length and the systems in differences, the estimation spans from 2003:06 through 2019:12 for the bivariate system, while for the trivariate the sample goes from 2003:05 through 2019:12. Hence, the number of observations in each sample is 198 and 199, respectively.

Table 4 – Information Criteria

	Bivariate System									
Lags	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
AIC	-3.81947	-3.82071	-3.8617	-3.87057	**-3.87624**	-3.85959	-3.83154	-3.81364	-3.83226	-3.81373
HQ	**-3.5867**	-3.56056	-3.57416	-3.55565	-3.53394	-3.4899	-3.43447	-3.38918	-3.38042	-3.33451
SC	**-3.24469**	-3.17831	-3.15168	-3.09293	-3.03098	-2.94671	-2.85104	-2.76552	-2.71652	-2.63037
FPE	**0.02196**	0.02194	0.021069	0.020894	**0.020789**	0.021155	0.021776	0.022192	0.021808	0.022245
	Trivariate System									
Lags	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
AIC	-1.51489	-1.49248	-1.53843	**-1.55329**	-1.54566	-1.50066	-1.43027	-1.41142	-1.4101	-1.41942
HQ	**-1.1452**	-1.06118	-1.04552	-0.99876	-0.92952	-0.8229	-0.6909	-0.61044	-0.5475	-0.4952
SC	**-0.60201**	-0.42745	-0.32126	-0.18398	-0.0242	0.172946	0.395483	0.566478	0.719947	0.862773
FPE	0.220191	0.225399	0.215553	**0.212726**	0.214802	0.225263	0.242437	0.247956	0.249354	0.248278

AIC: Akaike Information Criterion. SC: Schwarz Criterion.
HQ: Hannan-Quinn Criterion. FPE: Final Prediction Error Criterion.

Furthermore, Table 5 provides results from the residuals analysis. As shown, for any system or single equation it is possible to reject the null hypothesis on which each test is built. Therefore, it is possible to conclude that for both systems the estimations deliver residuals in accordance with the hypothesis that the VAR system is built on. The inclusion of the dummies for specific[9] events – previously mentioned – was necessary so that the hypothesis of normality of residues was not rejected both in single equations or in the multivariate case.

Table 5 – Residual Analysis.

	Bivariate System			**Trivariate System**			
	Single Equations		**VAR**	**Single Equations**			**VAR**
Ho[a]	IBC-Br	IPCA		IC-Br	IBC-Br	IPCA	
Homoscedasticity*	32.3%	8.2%	11.9%	17.8%	43.6%	8.0%	13.3%
Normality**	97.9%	36.4%	71.5%	10.3%	84.7%	88.5%	52.3%
No Serial Correlation***			25.3%				11.0%

*ARCH-LM test **Jarque-Bera test. *** Multivariate Portmanteau- and Breusch-Godfrey test.
[a] The values provided are the P-value of each test.

9 The three aditional dummies are: i) for the period of 2008:10 – 2008:12; ii) 2018:05; and iii) 2018:06.

4. Empirical Results.

In this section, an economic interpretation of the identification hypothesis is presented. Further, the Impulse Response and the Variance Decomposition are analyzed either for the bivariate and trivariate systems. Finally, the core inflation – following the methodology explained – is calculated.

4.1. Interpretation of the Identification Scheme.

The identification scheme described in appendix A takes into account some specific hypotheses. The first one, as described in section 2.4, is regarding the vertical long-run Phillips curve that, according to Quah and Vahey (1995), once the contracts have been fixed, positive shocks in core inflation are benign for the real economy in the short-run, albeit it has no impact in the activity level in the long-run. According to the methodology in use, the period in which this impact is different from zero is freely estimated from the data, thus allowing the researcher to assess the speed of adjustment to core inflation shocks.

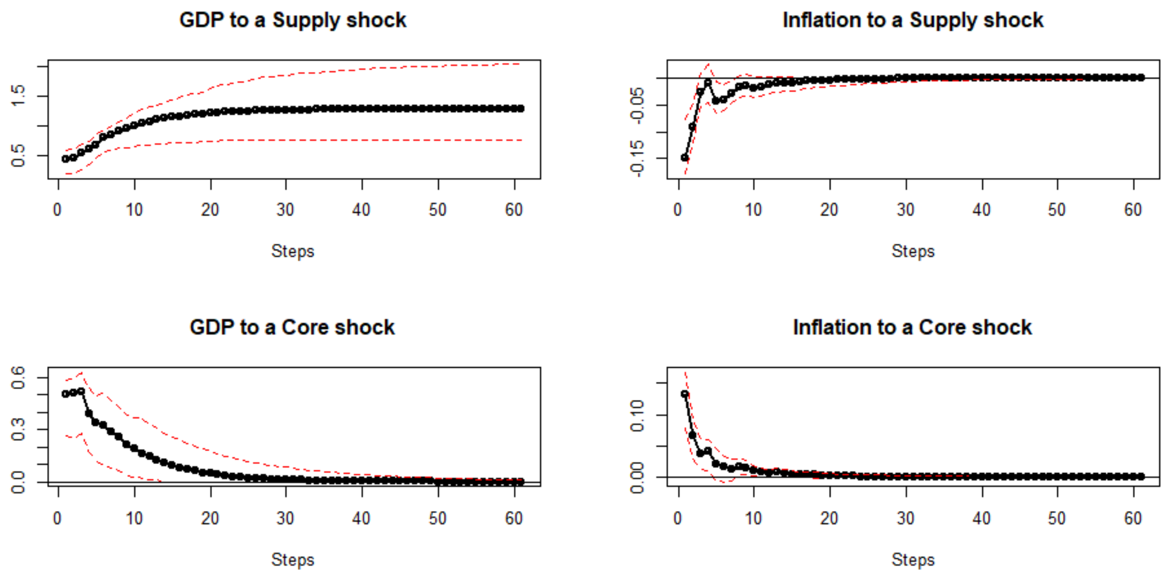
Also, it is important to note that no assumption is made about the impacts of non-core shocks on measured inflation, allowing the data to show us whether non-core shocks do not have a persistent impact on measured inflation. If so, as mentioned by Quah and Vahey (1995), the identification procedure is doubtful.

Finally, the orthogonality restriction, as described by Quah and Vahey (1995), does not allow for the structural shocks to be correlated in all lags and leads. Nevertheless, one may question this identify assumption, hence it is important to restate the argument presented both by Blanchard and Quah (1989) and Quah and Vahey (1995). The structural shock identified as the one that does impact the output level in the long-run could be originated by changes in the government policy (i.e. change in tax rates), the model does not restrict the possibility that this is caused by core inflation shocks, although does not allow for correlation. In other words, the orthogonality assumption does not restrict the channels by which core and non-core shocks impact output and inflation. Therefore, as argued in both papers, this assumption is approximately correct, and if it fails this happens only at specific points in time.

4.2. Impulse Response Analysis.

The impulse response functions – presented in Figures 3, 4, and 5 – track the dynamic response of output and inflation to an unanticipated one standard deviation shock of demand (core inflation), supply (non-core), and Commodity. The vertical axis corresponds to the log of the variables, and the horizontal axis shows the time in months for five years. Moreover, the dashed lines represent the uncertainty around the estimated coefficients[10].

Figure 3 – Impulse Response Analysis: Bivariate System.



Both shocks have a different directional impact on inflation, although in either case, the impact is temporary. A positive core (demand) shock increases inflation with the highest effect being at impact. Thereafter, the inflation rate mildly decreases until is statistically equal to zero after five months, when the demand shock is muted and inflation returns to the stationary level with a new price level equilibrium.

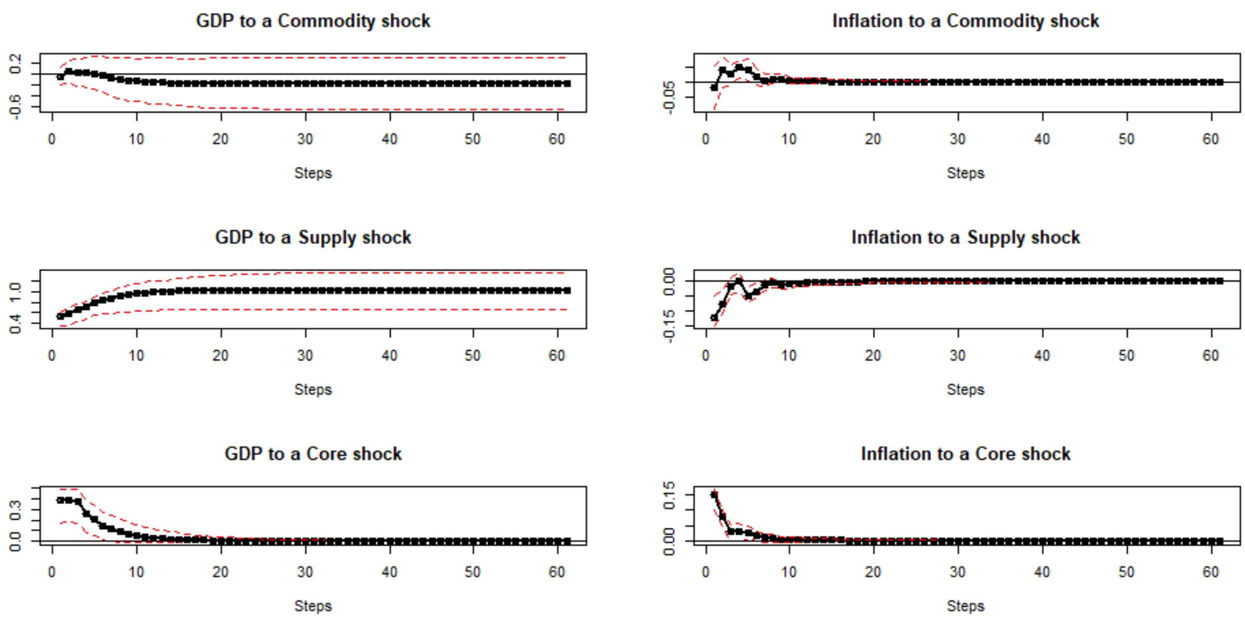
A supply (non-core) shock impacts the measured inflation in two steps; first, decreases inflation in the first quarter with the highest effect being at impact, then the effect starts to shrink until is statistically equal to zero in the fourth month. Secondly, from the fifth to sixth month, there is a second "wave" where it is possible to observe a new negative impact on inflation. Thereafter, the supply shock is mutated, and inflation converges to the stationary level, with a lower price level than before. Therefore, it is natural to note that a demand shock permanently increases the price level, whilst a supply shock decreases permanently the prices.

[10] 95% Bootstrap Confidence Interval, based on 1000 replications.

Turning the analysis to the impacts of both shocks on the output dynamics. A core (demand) shock will positively affect the level of output for almost one year when the effect statistically dies out, and the output returns to its long-run level. The speed of adjustment observed suggest two results: i) the output neutrality assumption seems valid, and ii) the short-run Phillips Curve in Brazil is near vertical, this result is similar to what Quah and Vahey (1995) estimated for the UK, and Martel (2008) found for Canada. In addition, a supply shock has a substantial impact on output level, increasing it until reaches a new long-run equilibrium between three and four years.

Figure 4 – which represents the Impulse Responses for the trivariate system – reinforces the results above discussed, and allow to trace impacts of a commodity shock in inflation and GDP.

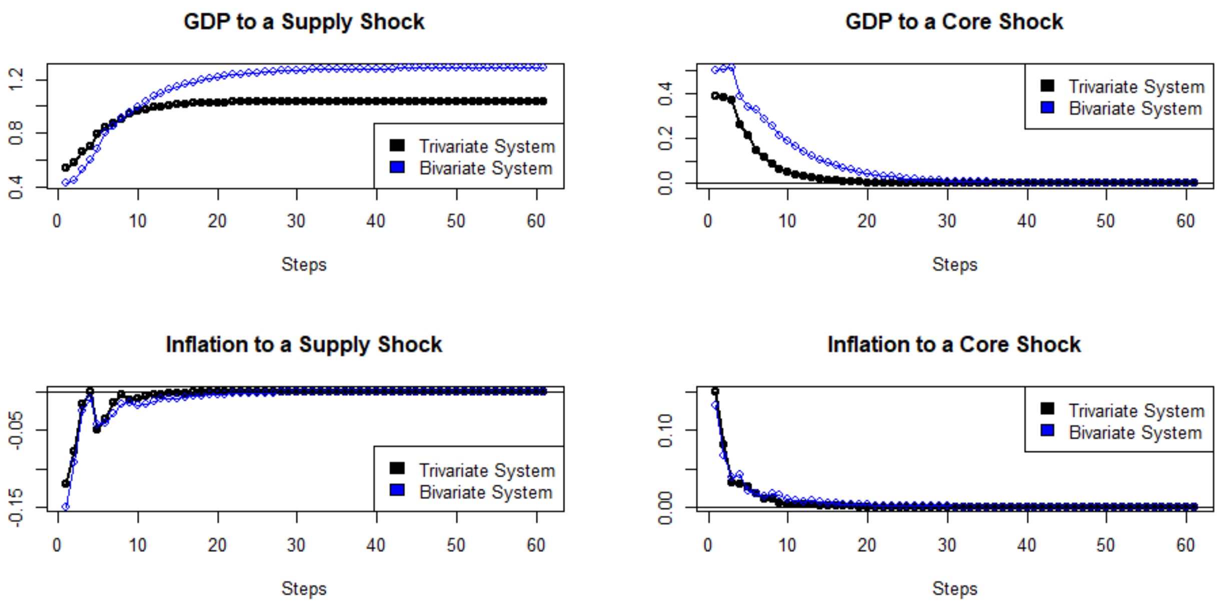
Figure 4 – Impulse Response Analysis: Trivariate System



A commodity shock seems to not have a statistically significant impact on output level, whilst positively impacts inflation from the fourth to the fifth month when the commodity shock dies out, and the inflation converges to the stationary level, with a higher price level in equilibrium.

Finally, it is possible to compare the impulse responses of both systems, as done in Figure 5. There is no relevant difference for the inflation dynamics in the face of any of the shocks. Nevertheless, in the bivariate system, the GDP reaches a higher long-run level in the presence of a supply shock, although in the trivariate system the convergence is fastest (i.e. one to two years earlier). This can be a result of the fact that usually, a commodity shock in Brazil is related to an improvement in the terms of trade which could also be transmitted as a productivity shock (i.e. a supply shock in the model used here), therefore when a commodity shock is added to the system it seems to be possible to separate both movements, while in the bivariate model there may be a sum of them as a supply shock. Albeit – as shown in Figure 4 – there is no statistical significance in the impulse response of GDP to a commodity shock, hence a more in-depth study on this relationship seems necessary, however, as the objective here is to analyze the core of inflation, this contradiction remains for future research.

Figure 5 – Impulse Response Analysis: Comparison of both systems.



Furthermore, due to a core shock, the GDP level seems to respond faster and with less intensity in the trivariate system than what is observed in the bivariate system (i.e an even stepper short-run Phillips Curve). Shedding light in what was described in section 2.4, that is, with the inclusion of commodity prices, it seems that we can better distinguish between what is “pure”/direct demand (core) shock, and what is a demand shock trough higher government revenues due to higher commodity prices.

4.3. Variance Decomposition.

The variance decomposition, as stated by Hahn (2002), calculates the percentage contribution of each structural shock to the variance of the h-step ahead forecast error of the variables. Table 6 provides this information for the measured inflation, and for the first (log) difference of GDP.

Table 6 – Variance Decomposition Analysis.

	Bivariate System				Trivariate System					
	Δ (log) GDP		Measured Inflation		Δ (log) GDP			Measured Inflation		
Months:	Non-Core	Core	Non-Core	Core	Commodity	Non-Core	Core	Commodity	Non-Core	Core
1	41.9%	58.1%	56.2%	43.8%	0.4%	66.4%	33.2%	1.1%	38.5%	60.4%
6	44.2%	55.8%	57.5%	42.5%	3.2%	63.4%	33.5%	10.7%	38.8%	50.5%
12	45.0%	55.0%	57.9%	42.1%	3.9%	62.8%	33.3%	10.8%	39.0%	50.2%
24	45.2%	54.8%	58.0%	42.0%	3.9%	62.8%	33.3%	10.9%	39.0%	50.2%
36	45.3%	54.7%	58.0%	42.0%	3.9%	62.8%	33.3%	10.9%	39.0%	50.2%
48	45.3%	54.7%	58.0%	42.0%	3.9%	62.8%	33.3%	10.9%	39.0%	50.2%
60	45.3%	54.7%	58.0%	42.0%	3.9%	62.8%	33.3%	10.9%	39.0%	50.2%

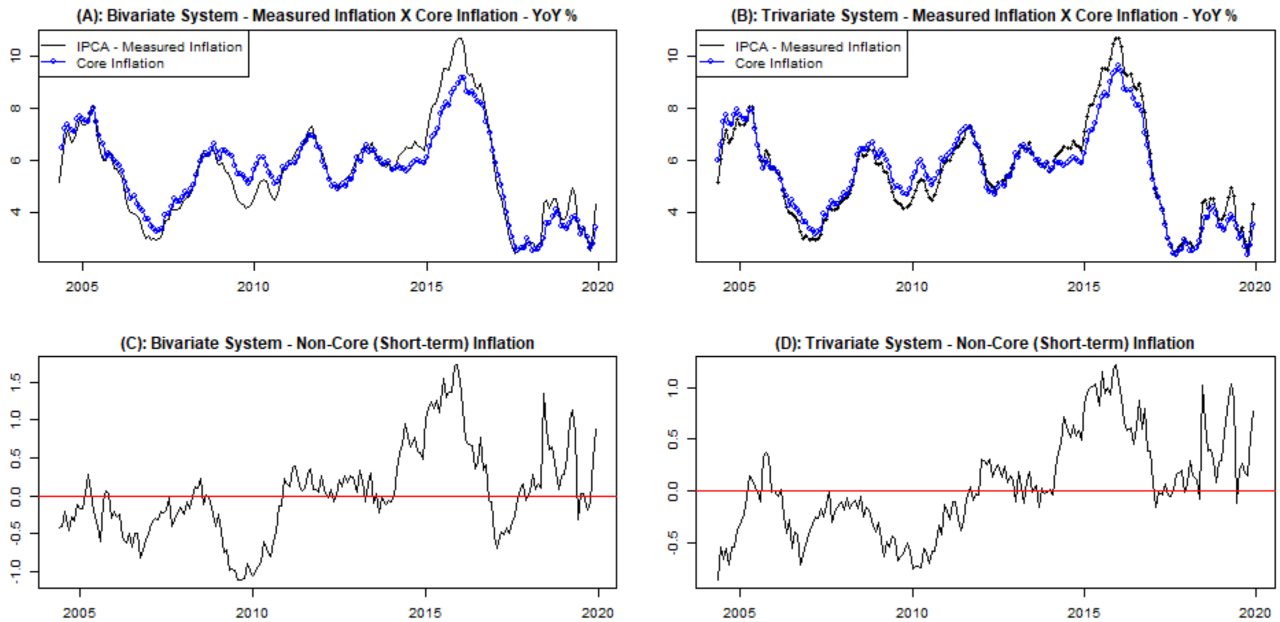
When analyzed the bivariate system, the most striking result is the high contribution that the non-core (supply) shocks have on the variance of the measured inflation, this could suggest that inflation in Brazil – during the estimation period – seems to be a phenomenon of supply rather than core (demand). Therefore, as commented by Gartner and Wehinger (1998), the identification scheme proposed by Quah and Vahey (1995) would need to be re-examined, once the core inflation calculated is not efficient in filter the price trend in the economy, that by definition, it should do.

Nevertheless, by introducing a commodity shock the results change substantially. The trivariate system shows that the core inflation shock is the key driver of measured inflation either in the short or in the long-run. Table 6 shown that core inflation accounting for 60.4% of the measured inflation variance in the short-run, and converges to 50.2% in the long-run. The remaining proportion of the variation in the long-run is given by non-core (supply), and commodity shocks each one accounting for 39% and 10.9%, respectively. In conclusion, the assumption that inflation is mainly a demand (core) phenomenon appears to be reasonable, thus the core inflation calculation through only demand shocks makes sense economically.

4.4. Estimated Core Inflation.

As noted in equations (2.4.11) and (2.4.13), it is possible to compute the core inflation as the time path of measured inflation in which the non-core shocks are imposed to be equal to zero, also this methodology is expanded here and the specific events – i.e. the dummies imposed to the residuals be normally distributed – are taking out of the core inflation computation. Figure 6 shows the results from the models estimated. The comparison with the measured inflation (IPCA) is done on a year-over-year basis with the corresponding short-term inflation (i.e. the non-core part of inflation).

Figure 6 – Measured Inflation (IPCA) and Both Core Measures Proposed.

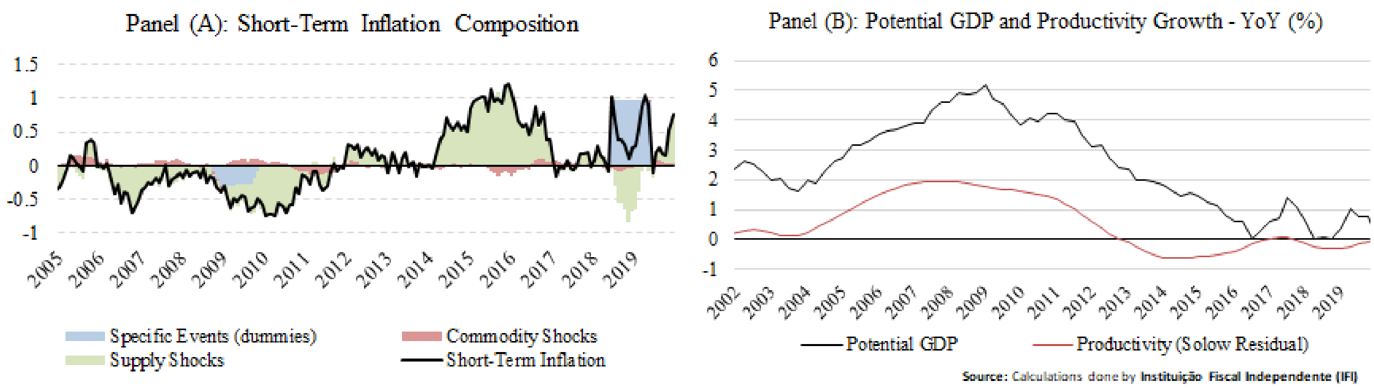


Visual inspection of panels A and B from Figure 6 suggests that the measured inflation and both core measures are very similar, thus showing some evidence that they follow the same trend[11]. This result is not a surprise, once it had already been anticipated by the variance decomposition analysis that the core inflation is the key driver of measured inflation.

Furthermore, Figure 6 depicts the short-term inflation in panels C and D. In the bivariate framework, this short-term inflation is driven only by supply shocks, whereas in the trivariate system these movements are explained by supply and commodity shocks. Even though, in the trivariate system, as suggested by the variance decomposition analysis, the short-term inflation – for the estimation period – is, mainly, due to supply shocks as the commodity shocks have, approximately, one-quarter of the supply shocks participation. Also, this result is more evident in Figure 7, in which the movements in short-term inflation are neatly due to supply shocks.

[11] A more formal test to evaluate this is provided in the next section. In which, both measures here calculated, and the ones used by the BCB are accessed for their capacity to track the trend of inflation.

Figure 7 – Short–Term Inflation (Trivariate System) and Potential GDP growth.



Some striking results can be drawn by analyzing Figures 6 and 7. In addition to core inflation and measured inflation seem to follow the same trend, it is possible to notice that the measured inflation is persistently below core inflation during positive supply shocks, such as the expansionary movement in productivity from 2004 to 2013. Consequently, measured inflation is above core inflation during negative supply shocks, such as the marginal decline in productivity from 2014 to the beginning of 2017. Therefore, it is noticeable that – even though core inflation and measured inflation follow the same trend – it is possible to both diverge significantly in the short-run. Using the frameworks explained, these differences can be from 1.7 p.p. (1.2 p.p.) to -1.1 (-0.9 p.p.) in the case of the bivariate (trivariate) system.

Furthermore, as the strong disinflation observed since the second half of 2016 – which brought the measured inflation over 10% to a range of 3% and 4% – was also followed by the core inflation, it is natural to conclude that this new inflation level seems to be more a structural movement than something caused only by short-term inflation.

5. Comparison to other Core Measures.

As was explained, in sections 2.2 and 2.3, a core inflation measure should be evaluated according to a specific range of criteria. This section aims to access some of these criteria for both core measures presented in section 4.3 and, at the same time, compare these measures with the ones followed by the BCB. To perform the analysis, all series are seasonally adjusted, annualized, and then the three-month moving average for each one is considered (henceforth, this will be referred to as SAAR 3MMA). Moreover, the measure *Average* is the average of all five core measures used by BCB, and not an average of the results on the tables. The same reasoning is applied for the variable *Average 2*, although this comprises the average of all seven measures presented in Table 7.

Therefore, following BCB (2020) and Machado *et al* (2020), each core measure will be accessed regarding five different characteristics: i) Volatility (each core measure should be less volatile than the IPCA), ii) Bias (relation between the average of each core measure and IPCA), iii) capacity to track the inflation trend (relation between each core and the centered moving average of the IPCA), iv) sensitivity to the business cycle, and v) forecast performance (each core measure should be more accurate than the IPCA).

5.1. Volatility.

Table 7 displays a summary of the main descriptive statistics for each core measure and IPCA. The period considered is from January 2007 to December 2019.

Table 7 – Main descriptive statistics for inflation core measures (SAAR 3MMA).

Core Methodology:	Core:	Mean:	Standard Deviation:	Maximum:	Minimum:	Bias:	Correlation with IPCA YoY:
Measured Inflation	**IPCA**	**5.57**	**2.59**	**14.17**	**-0.48**		**0.71**
SVARs (Backed by Economic Theory)	Core Measure (Bivariate System)	5.46	2.03	10.22	0.91	-0.11	0.77
	Core Measure (Trivariate System)	5.43	2.23	11.37	0.52	-0.13	0.72
Exclusion Methods	EX 0	5.22	1.93	8.97	0.65	-0.35	0.72
	EX 3	6.20	2.18	9.81	1.90	0.64	0.73
Statistical Cores	P55	5.62	1.82	9.33	1.36	0.05	0.84
	MS	5.14	1.72	9.28	1.97	-0.43	0.90
	DP	5.54	1.87	9.39	1.79	-0.03	0.84
	Average	5.86	1.73	8.92	2.68	0.29	0.88
	Average 2	5.62	1.76	9.27	2.29	0.05	0.88

Analysis of Table 7 provides the understanding that all core measures, except Ex 3[12] and P55, underestimate IPCA to different degrees. In absolute terms, the lowest bias is concentrated on the DP measure, whereas the highest is related to the Ex3 measure. Evaluating the results by groups, it is neatly that the core measures provided by the SVAR approach have a smaller bias than those calculated by Exclusion Methods. Still, the core measures based on statistical approaches are less biased, although the MS procedure presents a negatively high bias. Nevertheless, later on, a more sophisticated approach is used to test the statistical significance of these biases at different time horizons.

Furthermore, as expected, all the measures have lower volatility than the IPCA. The statistical cores are the most accurate measures in reducing the volatility, whereas the core inflation produced by the trivariate system produces the core inflation with the highest volatility, marginally above the Ex3 measure. Also, the statistical core measures have the highest correlation with annual changes in IPCA. Whilst the trivariate system and the exclusion methods have a similar degree of correlation when compared with IPCA (YoY), the bivariate core measure captures a greater correlation.

Finally, the comparison of the two *average* measures presented at the end of Table 7 shows the first sign that the inclusion of these SVAR measures in the set of core measures usually adopted by the BCB could be beneficial. As can be seen, the bias drop significantly, whilst the variance increases marginally.

5.2. Bias.

As proposed by Armour (2006) it is possible to use the Cogley equation to assess the bias of each core inflation.

$$\pi_{t+h} - \pi_t = \alpha_h + \beta_h(\pi_t - \pi_t^c) + \varepsilon_{t+h} \tag{5.2.1}$$

In which; π_{t+h} is the annual variation of headline inflation h months ahead, π_t is the SAAR 3MMA of the headline inflation, and π_t^c is the SAAR 3 MMA of each core measure. If we apply

[12] Overestimates the IPCA, on average, by 0.64 p.p. annually. This result should be related to the methodology employed in its calculation. The core measure Ex3 aggregates only industrial goods and services. Usually, the inflation from the services sector is, on average, higher than the IPCA headline. In addition, the industrial goods (core) inflation – resulted from the exclusion of specific items – as shown in BCB (2018a), have a higher average than before, therefore justifying this overestimation by the Ex3 measure.

the expectations operator to both sides of the equation (5.2.1), it is possible to write the equation as:

$$E[\pi_{t+h}] - E[\pi_t] = \alpha_h + \beta_h(E[\pi_t] - E[\pi_t^c]) \tag{5.2.2}$$

Therefore, if $\alpha_h = 0$ and $\beta_h = -1$, then $E[\pi_{t+h}] = E[\pi_t^c]$ and, as mentioned by Armour (2006), the core inflation is an unbiased predictor of total inflation. If α_h is smaller (greater) than zero, then inflation tends to be overestimated (underestimated) by the core. The term $(\pi_t - \pi_t^c)$ is understood as the short-term inflation or the transitory component of inflation, thus when $\beta_h = -1$ this component is completely filtered by the core measure. If β_h is smaller (greater) than -1 there is an overestimation (underestimation) of the future variation in inflation due to the short-term deviation. Essentially, following Armour (2006), this equation states that if the core inflation measure is below the headline inflation, then this means that the IPCA has been hit by a positive temporary shock that should be reversed in the future. Also, if there is a concomitant change in both headline inflation and the core measure, this could be interpreted as a permanent shock, since it can be incorporated as a shift in the mean of the series.

Table 8 shows the results of the estimation of equation (5.2.1) for each core measure considering $h = 0, 6, 12, 18$. The third column for each "h" shows the p-value for the F test in which the null hypothesis is $\alpha = 0$ and $\beta = -1$.

Table 8 – Bias test: Results estimation of equation 5.2.1

		h = 0			h = 6			h = 12			h = 18		
Core Methodology:	**Core:**	α	β+1	F test: α = 0; β = -1	α	β+1	F test: α = 0; β = -1	α	β+1	F test: α = 0; β = -1	α	β+1	F test: α = 0; β = -1
SVARs (Backed by Economic Theory)	Core Measure (Bivariate System)	0.12 (0.21)	-0.02 (0.12)	85.8%	0.12 (0.19)	0.07 (0.1)	53.5%	0.07 (0.39)	0.01 (0.16)	98.5%	0.08 (0.57)	-0.19 (0.29)	58.9%
	Core Measure (Trivariate System)	0.14 (0.27)	0.01 (0.23)	87.3%	0.16 (0.2)	-0.1 (0.18)	69.6%	0.11 (0.4)	-0.21 (0.31)	72.1%	0.11 (0.58)	-0.35 (0.52)	58.2%
Exclusion Methods	EX 0	0.21 (0.18)	0.41*** (0.04)	0.0%	0.16 (0.19)	0.53*** (0.06)	0.0%	0.19 (0.44)	0.38*** (0.08)	0.0%	0.13 (0.58)	0.25** (0.12)	7.9%
	EX 3	-0.4 (0.29)	0.37*** (0.08)	0.0%	-0.39** (0.19)	0.4*** (0.07)	0.0%	-0.55 (0.47)	0.23* (0.13)	2.5%	-0.8 (0.71)	0.02 (0.24)	26.9%
Statistical Cores	P55	-0.04 (0.21)	0.03 (0.09)	92.9%	-0.04 (0.17)	0.13* (0.08)	24.6%	-0.08 (0.4)	-0.16 (0.13)	45.1%	-0.16 (0.54)	-0.46** (0.21)	3.6%
	MS	0.45*** (0.16)	-0.03 (0.07)	1.2%	0.37* (0.2)	0.14 (0.09)	0.5%	0.45 (0.47)	-0.06 (0.13)	62.8%	0.48 (0.64)	-0.21* (0.12)	11.3%
	DP	0.04 (0.19)	-0.18* (0.11)	23.7%	0.05 (0.19)	-0.01 (0.12)	97.0%	0.01 (0.45)	-0.18 (0.16)	53.0%	-0.05 (0.61)	-0.47** (0.2)	2.5%
	Average	-0.27 (0.21)	0.06 (0.07)	18.4%	-0.23 (0.2)	0.19** (0.09)	4.5%	-0.33 (0.45)	-0.04 (0.1)	75.3%	-0.5 (0.61)	-0.29* (0.16)	16.7%
	Average 2	-0.02 (0.19)	-0.1 (0.09)	53.7%	-0.01 (0.19)	0.04 (0.1)	93.6%	-0.06 (0.44)	-0.2 (0.14)	35.4%	-0.16 (0.59)	-0.5** (0.21)	0.8%

*p<0.1; **p<0.05; ***p<0.01

Equations estimated by OLS w/ Heteroskedasticity and Autocorrelation robust standard errors (HAC).

At the 5% level of significance, the most striking result is that the only core measures consistently unbiased (i.e. in which α and β are, respectively, equal to 0 and -1 for different values of "h") are both SVAR core measures, whereas the other core measures used follow by the Central Bank seems to overestimate or underestimate the inflation.

5.3. Capacity to Track Trend Inflation.

Accordingly to BCB (2018a), the trend inflation is defined as the 12-month centered moving average of IPCA, therefore here it is used the same definition and the robustness of the results is also tested for the 18-month centered moving average.

To test the ability of each core to track the trend inflation, the mean absolute error (MAE) of each core measure was calculated in relation to the two centered moving averages. Table 9 show the results of these estimations, they are presented as a ratio between the MAE of each core and the one calculated using the headline inflation.

Table 9 – Capacity to track trend inflation.

	CMA 13	CMA 19
Core Measure (Bivariate System)	73.6%	74.1%
Core Measure (Trivariate System)	81.0%	83.0%
EX 0	94.8%	80.6%
EX 3	95.8%	86.9%
P55	63.3%	53.7%
MS	53.3%	48.1%
DP	60.7%	59.0%
Average	61.6%	52.4%
Average 2	53.8%	50.6%

The results have shown that the SVAR measures seem more accurate to track the trend inflation than the exclusion methods. Nevertheless, the statistical methods are the ones that produce results closer to the inflation trend with the MS procedure, by construction, being the most accurate among the seven core measures tested. Furthermore, comparing both averages it is neatly that the set including the SVAR measures has better adherence to the inflation trend.

5.4. Sensitivity to the Business Cycle.

To test for the sensitivity of each core measure to the business cycle three different exercises were performed. The first one analyzes the contemporaneous correlation (five-year rolling window) between each core measure and the output gap[13]. The results are shown in Figure 8 - panel A.

The second one estimates the equation 5.4.1. The results are depicted in Figure 8 – panel B.

$$\pi_t^c = \alpha + \beta\, h_{t-i} + \varepsilon_t;\ i = 0,1,2,3,4,5,6 \qquad (5.4.1)$$

Whereas, as done by Machado *et al* (2020), the third exercise is more elaborate by estimating a quarterly hybrid New-Keynesian Phillips Curve. The results are displayed in Figure 8 – panel c.

$$\pi_t^c = \alpha_0 + \alpha_1\pi_{t-1} + \alpha_2 E(\pi_{t+1}) + (1 - \alpha_1 - \alpha_2)\pi^* + \gamma h_{t-4} + \sum_{i=1}^{3}\beta_i D_i + \varepsilon_t \qquad (5.4.2)$$

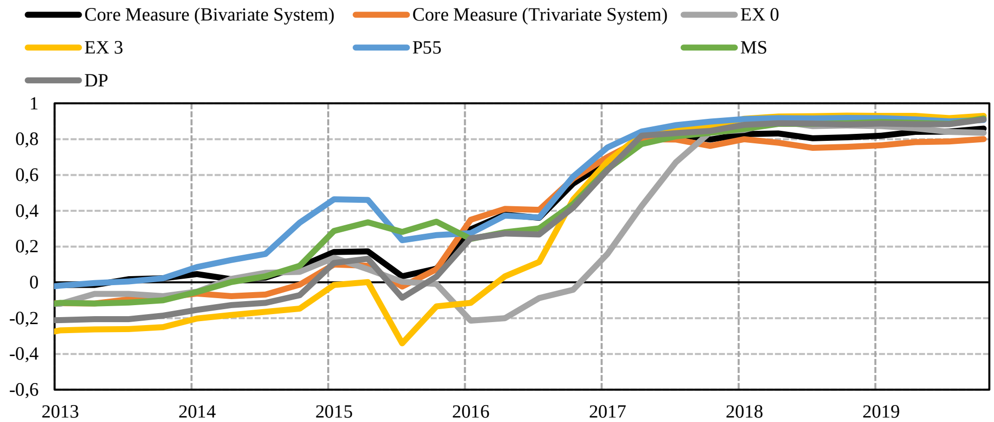
In which, π_{t-1} is the headline inflation lagged one quarter, $E(\pi_{t+1})$ is the one-quarter ahead IPCA expectation from FOCUS survey, π^* is the foreign inflation[14], h_{t-4} is the output gap calculated by IPEA lagged four quarters, and D_i are the seasonal dummies.

All three exercises seem to have reached the same conclusion, all core measures have a positive and significant sensitivity to the business cycle. Also, the core measure identified as Ex3 has the greatest sensitivity to the business cycle as was the objective of BCB in its construction, although when we consider the level of uncertainty to which each exercise is subject, there does not appear to be any statistically significant difference between each core measure with respect to the sensitivity to business cycles.

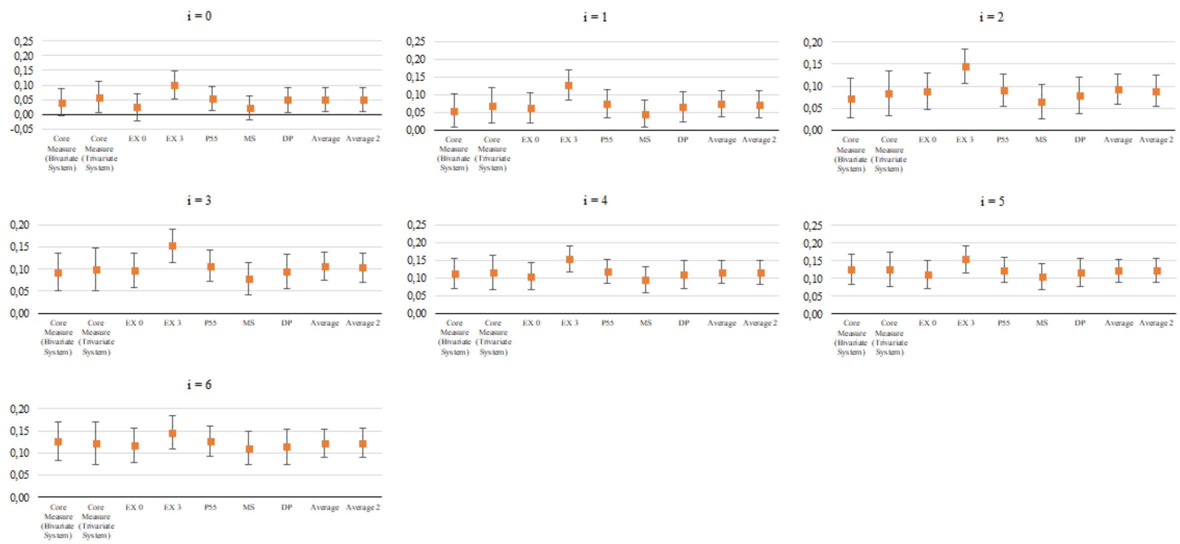
Further, is striking the result that the correlation between each measure of core inflation and the output gap started to increase at the beginning of 2016 and reached values between 0.80 and 0.92 coming from negative values throughout 2013 and 2014. This seems to be a positive result due to the implementation of a more responsible fiscal policy since the second half of 2016, as well as the improvement in BCB communication, although further research may help to better understand this.

[13] Calculated by IPEA following the methodology explained by Júnior (2017).
[14] Where IC-br is used as proxy for this variable (see footnote 4 for more details).

Figure 8 – Sensitivity of each core measure to the Business cycle.



Panel (A) – Contemporaneous correlation (five-year rolling window) between each core measure and the output gap.

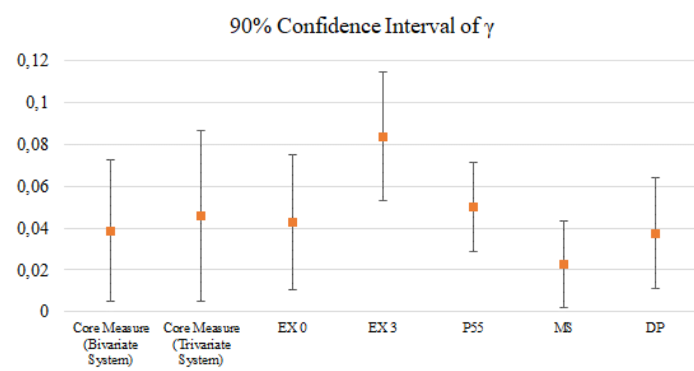


Panel (B) – Results from the estimation of equation (5.4.1). **90% Confidence Interval of the parameter β.**

	γ	SE (γ)	p-value
Core Measure (Bivariate System)	0.039	0.02	5.8%
Core Measure (Trivariate System)	0.045	0.02	7.0%
EX 0	0.043	0.02	3.6%
EX 3	0.084	0.02	0.0%
P55	0.050	0.01	0.0%
MS	0.023	0.01	7.7%
DP	0.037	0.02	2.5%
Average	0.047	0.01	0.0%
Average 2	0.046	0.01	0.1%

Equations estimated by TSLS w/ Heteroskedasticity and Autocorrelation robust standard errors (HAC).

As instruments, the lagged variables were used.



Panel (C) – Results from the estimation of equation (5.4.2). Appendix B shows the estimation of all coefficients in equation (5.4.2)

5.5. Forecast Performance (out-of-sample).

The forecast performance is measured by rewriting the equation 5.2.1 as the following.

$$\pi_{t+h} = \alpha_h + \beta_h \pi_t^c + (1-\beta_h)\pi_t + \varepsilon_{t+h} \tag{5.5.1}$$

Therefore, as Armour (2006) explained, it is possible to measure to what extent - in comparison to using only the current level of headline inflation - each core measure improves the explanation of future inflation. So, the exercise consists of first use the equation 5.5.1 setting $\beta_h = \alpha_h = 0$, then make the forecast of π_{t+h} for the period of January/16 – December/19. After, the MAE of this result is computed in relation to the observed π_{t+h}.

The second step goes through estimate[15] the equation 5.5.1 including individually each core measure (i.e. the values of $\alpha_h$and β_h are estimated), then the out-of-sample forecast is made for the same horizon as before, and the MAE for each forecast is computed.

Finally, the results are presented as a ratio between the MAE of the second step and the first step, so it is possible to access to which degree each core measure helps to reduce the mean absolute error of using only the headline inflation to explain the future variation in inflation. Figure 9 – panel A depicts these results.

Furthermore, these results are tested for whether there is a statistically significant difference. In order to that, the Diebold and Mariano test was performed and the results are shown in Figure 9 – panel B.

Figure 9 – Forecast Performance and the Diebold and Mariano test.

	h = 6	**h = 12**	**h = 18**
Core Measure (Bivariate System)	65.2%	91.9%	92.4%
Core Measure (Trivariate System)	71.8%	89.4%	86.9%
EX 0	72.3%	80.5%	82.3%
EX 3	65.9%	77.7%	84.0%
P55	64.3%	80.2%	80.6%
MS	68.4%	89.2%	97.2%
DP	67.1%	83.4%	84.0%
Average	60.3%	76.5%	76.5%
Average 2	53.7%	77.9%	79.9%

Training sample: Jan/07 – Dec/15.
Forecasting sample: Jan/16 – Dec/19.

Panel (A) – Ratio between both approaches.

	h = 6	**h = 12**	**h = 18**
Core Measure (Bivariate System)	0.2%	13.6%	37.1%
Core Measure (Trivariate System)	0.1%	2.0%	3.5%
EX 0	0.3%	3.4%	14.4%
EX 3	0.8%	0.4%	2.7%
P55	0.4%	2.5%	8.1%
MS	0.7%	37.8%	89.7%
DP	1.0%	14.1%	42.7%
Average	0.3%	2.0%	10.6%
Average 2	0.2%	2.1%	12.0%

Null hypothesis: similar predictive capacity between IPCA and each core inflation measure.

Panel (B) – Diebold Mariano test (p-value).

[15] Estimation period span through 2007/01 – 2015/12.

The results have shown that - when h is small (i.e. equal to 6) – all core measures helped to reduces the MAE (of forecasting using only the IPCA) to a similar degree. At higher values of h, this result breaks down, that is, the only core measures that consistently present statistically significant results showing a reduction of the MAE are: i) the SVAR measure (based on the trivariate approach), ii) the Ex3, and iii) the P55.

6. Conclusion.

Figueiredo (2001) states that a Central Bank operating under an Inflation Target regime should use a measure of core inflation, to either detect particular movements in prices or conduct official communication more transparently. Although this argument seems to have reached a consensus, there is no convergence on what is the best methodology for estimating this unobserved component. Facing this Laflèche (1997) argues that the most suitable strategy would be to use a set of core measures estimated from different methodologies, thus a convergence in this group should be a reliable sign to the monetary policy authority.

The analysis of a selected group of economies showed that there was a convergence to the idea of using more than one core measure (as shown in Table 2), the methodologies most used involve the Exclusion methods and the statistical methods. Nevertheless, these methods are based on remove in some *ad* hoc manner the noise component, so a part of the Central Banks in the sample analyzed uses also economics and econometrics models to have a more robust estimation of the core inflation, this is not observed for the Central Bank of Brazil.

Based on these arguments, the main objective of this paper was to develop a new core measure for the Brazilian economy. In addition to the atheoretical approaches used by the Central Bank of Brazil, this new core measure is calculated by imposing the long-run verticality of the Phillips Curve both in a bivariate and trivariate SVAR. Therefore, with this methodology rather than subjective eliminated determined shocks they are systematically and intrinsically removed by the identification assumption underlying the model.

In light of the results, it is possible to conclude that the main source of divergence between the measured inflation and each SVAR core measure is due to the presence of supply shocks. In the bivariate system, this result is straightforward, however, the confirmation by the trivariate system enables the understanding of how the short-term inflation behaves, hence it is possible to assess based on the type and magnitude of each supply shock how the convergence between measured inflation and core measures will occur.

Furthermore, albeit the SVAR measures are not so eased understandable by the public in general (as the exclusion methods) - according to the results presented before - they are the only ones systematically unbiased, that is, at different time horizons, the future variations of the IPCA tend to converge to the current value of the core inflation. In addition, the SVAR measures showed more gains in capture the trend inflation than the exclusion methods. Also, there is no statistical difference among the seven measures studied regarding the sensitivity to business cycles. Finally, to what concern the (out-of-sample) forecasting performance the only core measures with consistent and statistically better performance than using only the current level of IPCA to forecast the future variation of IPCA at different time horizons are: i) the SVAR measure (based on the trivariate approach), ii) the Ex3, and iii) the P55.

Together, the results demonstrated the argument of Laflèche (1997), each core measure has a distinct advantage when compared to each other, so the use of a set of core measures seems the most reasonable choice. In this sense, the analysis of the gains with the adoption of the SVAR methodology signals that this is a useful indicator to be part of the set followed by the Central Bank of Brazil.

7. References

Armour, Jamie (2006). **An Evaluation of Core Inflation Measures.** Bank of Canada Working Paper 2006 – 10.

BCB (2010). **Transfer of Commodity Prices to the IPCA and Commodities Index-Brazil.** BCB Inflation Report, December 2010.

BCB (2017). **Methodological revision of the Commodities Index – Brazil (IC-Br).** BCB Inflation Report, December 2017.

BCB (2018a). **New Core Inflation Measures.** BCB Inflation Report, June 2018.

BCB (2018). **Exchange Rate Pass-Through From the Perspective of a Semi-structural Model.** BCB Inflation Report, September 2018.

BCB (2020a). **Update of the set of core inflation measures commonly considered by the BCB for economic outlook analysis.** BCB Inflation Report, June 2020.

Benati, Luca (2015). **The Long-Run Phillips Curve: A Structural VAR Investigation.** Department of Economics, University of Bern. Switzerland.

Biondi, Roberta Loboda & Junior, Roberto Toneto (2005). **O Desempenho dos Países que Adotaram o Regime de Metas Inflacionárias: uma Análise Comparativa.** São Paulo. USP

Blanchard, O. J. and Quah, Danny (1989). **The Dynamic Effect of Aggregate Demand and Supply Disturbances.** The American Economic Review, Vol. 79, No. 4, pp. 655-673.

Bjørnland, Hilde (2000). **Identifying Domestic and Imported Core Inflation.** IMF Working paper.

Bryan, Michael and Cecchetti, Stephen G. (1993). **Measuring core inflation**. National Bureau of Economic Working Paper 4303.

Bryan, Michael F. and Cecchetti, Stephen G. (1993). **The Consumer Price Index as a measure of inflation**. Federal Reserve Bank of Cleveland Economic Review, 15-24.

Bryan, Michael and Cecchetti, Stephen G. (1996). **Inflation and the distribution of price changes**. National Bureau of Economic Working Paper 5793.

Bogdanski, J. and Freitas, P. and Goldfajn, I. and Tombini, A. (2001). **In‡ation Targeting in Brazil: Shocks, Backward Looking Prices, and IMF Conditionality.** Programa de Seminários Acadêmicos do IPE/USP, Seminário n.07/2001.

Cecchetti, Stephen G. (1997). **Measuring inflation for central bankers.** Federal Reserve Bank of St. Louis Review, 79, 143-155.

Cristadoro, R., Forni, M., Reichlin, L. & Veronese, G. (2005). **A Core Inflation Indicator for the Euro Area**. Journal of Money, Credit and Banking, Vol. 37, No. 3, pp. 539-560.

Da Silva, Nelson (2020). **Medida de Núcleo de Inflação para o Brasil baseadas no Método Wavelets.** Working Paper Series 528. Central Bank of Brazil.

Deustche Bundesbank (2000). **Core inflation rates as a tool of price analysis**. Deustche Bundesbank Monthly Report.

Dickey, D. A. and Fuller, W. A. (1981). **Likelihood Ratio Statistics for Autoregressive Time Series with a Unit Root**, Econometrica, 49, 1057–1072.

ECB (2018). **Measures of Underlying Inflation for the Euro Area**. In ECB Economic Bulletin 4/2018.

Falk, Barry and Lee, Bong-Loo (1999). **Revisiting the Phillips Curve with a structural VAR.** Economic Staf Paper Series. Iowa State University. Digital Repository.

Figueiredo, F. M. R. (2001). **Evaluating Core Inflation Measures for Brazil**. Working Papers Series 14. Central Bank of Brazil.

Galí, Jordi (2008). **Monetary Policy, Inflation and the Business Cycle: An Introduction to the New Keynesian framework.** Book. Princeton University Press.

Gartner, Christine and Wehinger, D. Gert (1998). **Core inflation in selected European Union Countries**. Working Paper 33. Oesterreichische National Bank.

Hahn, Eike (2002). **Core Inflation in the Euro Area: Evidence from the Structural VAR Approach.** CFS Working Paper Nº. 2001/09.

Hamilton (1994). **Time Series Analysis.** Princeton University Press.

Júnior, José Ronaldo de Castro Souza (2017). **Produto Potencial e Hiato do Produto: nível atual e projeções para 2018.** IPEA. Carta de Conjuntura Nº 36.

Laflèche, Thérèse (1997). **Statistical measures of the trend rate of inflation**. Bank of Canada Review, Bank of Canada, vol. 1997 (Autumn), pages 29-47.

Machado, V. da G. and Nadal, Raquel and Kawaoka, F. R. R. (2020). **A Data-Rich Measure of Underlying Inflation for Brazil.** Working Papers Series 516. Central Bank of Brazil.

Martel, Sylvain (2008). **A Structural VAR Approach to Core Inflation in Canada**. Bank of Canada Discussion Paper 2008-10.

Mattos, D. (2018). **Core inflation estimation via score driven models**. Master’s thesis – PUC/RJ.

Marques, C. R. and Neves, P. D. and Sarmento, L. M. (2000). **Evaluating core inflation indicators**. Working Paper 3-00, Economics Research Department, Banco de Portugal.

Osterwald-Lenum, M. (1992). **A Note with Quantiles of the Asymptotic Distribution of the Maximum Likelihood Cointegration Rank Test Statistics**. Oxford Bulletin of Economics and Statistics, 55, 3, 461–472.

Quah, D. and Vahey, S. (1995). **Measuring Core Inflation**. Economic Journal, Vol. 105, No. 432, pp. 1130 – 1144.

Rich, R. & Steindel, C. (2005). **A Review of Core Inflation and an Evaluation of its Measures**. FRBNY Staff Report 236. Federal Reserve Bank of New York.

Schwartzman, Felipe Sarah (2006). **Estimativa de Curva de Phillips para o Brasil com preços desagregados.** Economia aplicada. Vol. 10. nº 1.

Silva Filho, T. N. T. and Figueiredo, F. M. R. (2011). **Has Core Inflation Been doing a Good Job in Brazil.** Revista Brasileira de Economia, Vol. 65, No 2.

Silva Filho, T. N. T. and Figueiredo, F. M. R. (2014a). **A Volatility and Persistence-Based Core Inflation.** Working Papers Series 367. Central Bank of Brazil.

Silva Filho, T. N. T. and Figueiredo, F. M. R. (2014b). **Revisitando as Medidas de Núcleo de Inflação do Banco Central do Brasil.** Discussion Papers Series 356. Central Bank of Brazil.

Picchetti, P and Kanczuk, F. (2001). **An Application of Quah and Vaheys SVAR Methodology for Estimating Core Inflation in Brazil**. Anais do XXIX encontro nacional de economia [proceedings of the 29th brazilian economics meeting], ANPEC - Associação Nacional dos Centros de Pós Graduação em Economia [Brazilian Association of Graduate Programs in Economics].

Wynne, Mark A. (1999). **Core Inflation: A review of Some Conceptual Issues.** Federal Reserve Bank of Dallas. Research Department.

Appendix A – The Bivariate and Trivariate SVAR approach.

Formally, using the bivariate SVAR, it is possible to describe the methodology as follows. First, let y be the logarithm of output and π denote the measured inflation rate with ε_1 and ε_2 being the structural shocks influencing the system, then by denoting $x_t = (\Delta y_t, \pi_t)$ [16] the structural representation of the VAR model with order p can be written as:

$$A(L)x_t = \varepsilon_t \qquad (2.4.3)$$

Where the coefficient matrix $A(L) = \sum_{j=0}^{p} A(j)L^j$ is assumed to be invertible, and $Var(\varepsilon_t) = I$. Then the VMA specification of the model is given by equations (2.2.4) and (2.2.5); where $D(L) = A(L)^{-1}$.

$$x_t = D(L)\varepsilon_t \qquad (2.2.4)$$

$$\begin{aligned} x_t &= D(0)\varepsilon_t + D(1)\varepsilon_{t-1} + \cdots \\ &= \sum_{j=0}^{\infty} \boldsymbol{D(j)\varepsilon_{t-j}} \end{aligned} \qquad (2.4.5)$$

Hence, the equation (2.4.4) expresses Δy_t and π_t as a function of the lags of the two structural shocks. The long-run output neutrality is achieved by imposing that $\sum_{j=0}^{\infty} d_{12}(j) = 0$[17]. Then, by decomposing the movements in the measured inflation as:

$$\pi_t = \sum_{j=0}^{\infty} d_{21}(j)\, \varepsilon_{1,t-j} + \sum_{j=0}^{\infty} d_{22}(j)\, \varepsilon_{2,t-j} \qquad (2.4.6)$$

We can write the core inflation, following their definition, as: $\pi_t^c = \sum_{j=0}^{\infty} d_{22}(j)\, \varepsilon_{2,t-j}$.

Due to a simultaneity problem, the structural shocks and the coefficients of the matrix $D(L)$ can not be directly identified, thus it is necessary to estimate the reduced form as expressed in (2.4.7), with the variance-covariance matrix of the residuals given by $E(e_t e_t') = \Omega$

[16] Actually, when explaining the model, Quah and Vahey (1995) uses $\Delta\pi_t$ as they assume that y and π have stochastic trends, however are not cointegrated. Although, while they explain the variables used in the estimation, $\Delta\pi_t$ is referred to the change in the (log of) RPI – Retail Price Index, therefore it is understandable that π is referred to the price index in which the inflation rate is calculated.

[17] Remmeber the inverse solution of equation (2.4.2), that is, $1/\varphi \rightarrow 0$.

$$B(L)x_t = e_t \tag{2.4.7}$$

Then, assuming that (2.4.7) is stationary and inverting $B(L)$ provide us the equation (2.4.8) - the Wold-moving average formulation of equation (2.4.7), where $C(0) = I$.

$$x_t = C(L)e_t \tag{2.4.8}$$

Associating equations (2.4.4) and (2.4.8) allows us to establish the following relation between the reduced form shocks and structural shocks: $e_t = D(0)\varepsilon_t$, and $D(j) = C(j)D(0)$. Therefore, as we already estimated all the $C(j)$ we just need to identify $D(0)$ in order to recover the structural shocks from the reduced forms and all $D(j)$.

Once a bivariate SVAR is being considered we will need to identify four different parameters that shape the matrix $D(0)$. Furthermore, the variance-covariance matrix of both forms will be related as shown in equation (2.4.9), and this will provide three restrictions for the identification procedure. The fourth restriction that allows the full identification of $D(0)$ is related to the neutrality condition ($\sum_{j=0}^{\infty} d_{12}(j) = 0$).

$$E(e_t e_t') = D(0)\varepsilon_t \varepsilon_t' D(0)' = \Omega \xrightarrow{Var(\varepsilon_t) = I} D(0)D(0)' = \Omega \tag{2.4.9}$$

In summary, as shown by Martel (2008), the methodology proposed by Quah and Vahey (1995) can be simplified in the system (2.4.10)

$$\begin{bmatrix} \Delta lnY_t \\ \pi_t \end{bmatrix} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} + \sum_{j=0}^{\infty} \begin{bmatrix} d_{11,j} & d_{12,j} \\ d_{21,j} & d_{22,j} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-j} \\ \varepsilon_{2,t-j} \end{bmatrix} \tag{2.4.10}$$

Then, the long-run restriction is imposed through $\sum_{j=0}^{\infty} d_{12,j} = 0$, so ε_2 do not impact the output level in the long-run, implying that the core inflation is:

$$\pi_t^c = v_2 + \sum_{j=0}^{\infty} d_{22,j}\, \varepsilon_{2,t-j} \tag{2.4.11}$$

A plausible criticism regard this methodology argues that Quah and Vahey (1995) consider inflation and output as the only two shocks that affect the economy. Therefore, other methodologies sought to expand the structural VAR to consider more possible shocks.

In light of what was explained before, Bjørnland (2000) and Martel (2008) add a third shock to the system in order to identify the effects of an energy price shock in Norway and Canada, respectively. Bjørnland (2000) uses oil prices, whereas Martel (2008) uses the energy component of the Bank of Canada commodity price index. Initially done by Bjørnland (2000) the justification to implement this component is that an energy price shock might have real effects, and this can come from two different economics views; i) higher energy prices should affect output through the aggregate production function reducing the quantity of energy used during the production. Moreover, higher energy prices could affect the inflationary expectations of economic agents at a point that they will demand higher wages, then affecting inflation. Also, ii) the effects of an energy shock will depend on the government response, that is, if the country is considered a small exporter, then higher energy prices will increase the government revenues allowing them to use a more expansionary policy boosting the demand and, consequently, positively impacting inflation.

To implement this shock in the structural VAR model both authors suppose that only energy shock can affect the energy prices in the long-run[18], while the neutrality condition remains the same. Therefore, keeping the same notation as before we have the following model structure:

$$\begin{bmatrix} \Delta lnEnerg_t \\ \Delta lnY_t \\ \pi_t \end{bmatrix} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix} + \sum_{j=0}^{\infty} \begin{bmatrix} d_{11,j} & d_{12,j} & d_{13,j} \\ d_{21,j} & d_{22,j} & d_{23,j} \\ d_{31,j} & d_{32,j} & d_{33,j} \end{bmatrix} \begin{bmatrix} \varepsilon_{1,t-j} \\ \varepsilon_{2,t-j} \\ \varepsilon_{3,t-j} \end{bmatrix} \tag{2.4.12}$$

The economics restriction that the energy price shock is the only one influencing the energy prices is implemented in the system by $\sum_{j=0}^{\infty} d_{12,j} = 0$ and $\sum_{j=0}^{\infty} d_{13,j} = 0$, while the long-run verticality of the Phillips curve is imposed by $\sum_{j=0}^{\infty} d_{23,j} = 0$. Hence, the core inflation is given by the following expression:

$$\pi_t^c = v_3 + \sum_{j=0}^{\infty} d_{33,j}\, \varepsilon_{3,t-j} \tag{2.4.13}$$

[18] What give us two additional restrictions to the identification procedure. It is worth to notice that the identification of matrix $D(0)$ in a system with n variables requires n^2 restrictions. The relation $D(0)D(0)' = \Omega$, and the assumption that Ω is symmetric give us a total of $\frac{n(n+1)}{2}$ restrictions, while the remain $\frac{n(n-1)}{2}$ are given by economic theory such as the neutrality condition.

Appendix B – Equation (5.4.2) estimations results.

	Core Measure (Bivariate System)			Core Measure (Trivariate System)			Ex0		
	Estimation	SE	p-value	Estimation	Std. Error	p-value	Estimation	Std. Error	p-value
α_0	0.18	0.12	13.6%	0.12	0.14	39.4%	-0.38	0.11	0.2%
α_1	0.29	0.09	0.3%	0.20	0.11	7.6%	0.21	0.09	1.0%
α_2	0.68	0.09	0.0%	0.76	0.11	0.0%	0.78	0.09	0.0%
$1\text{-}\alpha_1 - \alpha_2$	0.02	0.01	2.8%	0.03	0.01	0.6%	0.01	0.01	1.5%
γ	0.04	0.02	5.8%	0.05	0.02	7.0%	0.04	0.02	3.6%
β_1	0.39	0.17	2.7%	0.46	0.21	3.1%	0.46	0.16	0.8%
β_2	-0.10	0.20	61.8%	0.03	0.25	89.0%	0.83	0.20	0.0%
β_3	-0.63	0.15	0.0%	-0.54	0.19	0.6%	0.62	0.15	0.0%

	Ex3			P55			MS		
	Estimation	Std. Error	p-value	Estimation	Std. Error	p-value	Estimation	Std. Error	p-value
α_0	0.17	0.11	11.6%	-0.05	0.07	53.9%	0.01	0.07	88.7%
α_1	0.25	0.08	0.5%	0.22	0.06	0.1%	0.31	0.06	0.0%
α_2	0.74	0.08	0.0%	0.76	0.06	0.0%	0.68	0.06	0.0%
$1\text{-}\alpha_1 - \alpha_2$	0.01	0.01	15.7%	0.01	0.01	2.1%	0.01	0.01	8.4%
γ	0.08	0.02	0.0%	0.05	0.01	0.0%	0.02	0.01	7.7%
β_1	0.08	0.16	62.7%	0.41	0.11	0.1%	0.14	0.10	17.7%
β_2	0.37	0.19	5.5%	0.42	0.13	0.3%	0.24	0.13	6.1%
β_3	-0.33	0.14	2.5%	-0.16	0.10	11.4%	-0.19	0.10	5.4%

	DP			Average			Average2		
	Estimation	Std. Error	p-value	Estimation	Std. Error	p-value	Estimation	Std. Error	p-value
α_0	0.08	0.09	37.1%	-0.03	0.06	63.0%	0.02	0.07	78.5%
α_1	0.26	0.07	0.1%	0.26	0.05	0.0%	0.25	0.06	0.0%
α_2	0.72	0.07	0.0%	0.74	0.05	0.0%	0.73	0.06	0.0%
$1\text{-}\alpha_1 - \alpha_2$	0.02	0.01	1.3%	0.01	0.01	20.7%	0.01	0.01	3.9%
γ	0.04	0.02	2.5%	0.05	0.01	0.0%	0.05	0.01	0.1%
β_1	0.20	0.13	13.8%	0.26	0.09	0.9%	0.31	0.11	0.7%
β_2	0.20	0.16	21.5%	0.41	0.11	0.1%	0.29	0.13	3.1%
β_3	-0.26	0.12	4.4%	-0.06	0.09	45.9%	-0.21	0.10	3.4%

Equations estimated by TSLS w/ Heteroskedasticity and Autocorrelation robust standard errors (HAC).
As instruments, the lagged variables were used.